

Machine Learning Operations Semester

Project-Task 3

Environmental Monitoring and Pollution Prediction System



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1. Introduction

This report outlines the implementation of a monitoring environment for a machine learning (ML) model served through a Flask API. The primary goal is to ensure real-time monitoring and observability of the model's performance and system metrics. Prometheus and Grafana were used to set up a robust monitoring stack to collect, query, and visualize metrics.

2. Objectives

The key objectives of this setup are:

- Monitor the ML model's inference performance, including latency and throughput.
- Track resource utilization (CPU, memory, etc.) of the Flask API hosting the model.
- Enable real-time visualization and alerts for critical metrics.
- Provide insights into system health and model efficiency.

3. Methodology

3.1. Task 3 Part 1-Set up Monitoring

The monitoring environment is built around the following components:

- **Flask API:** Serves the ML model and exposes metrics endpoints.
- **Prometheus:** Collects metrics from the Flask API and the system.
- **Grafana:** Visualizes the metrics and sets up alerts.

3.2. Prometheus Setup

1. Installing Prometheus:

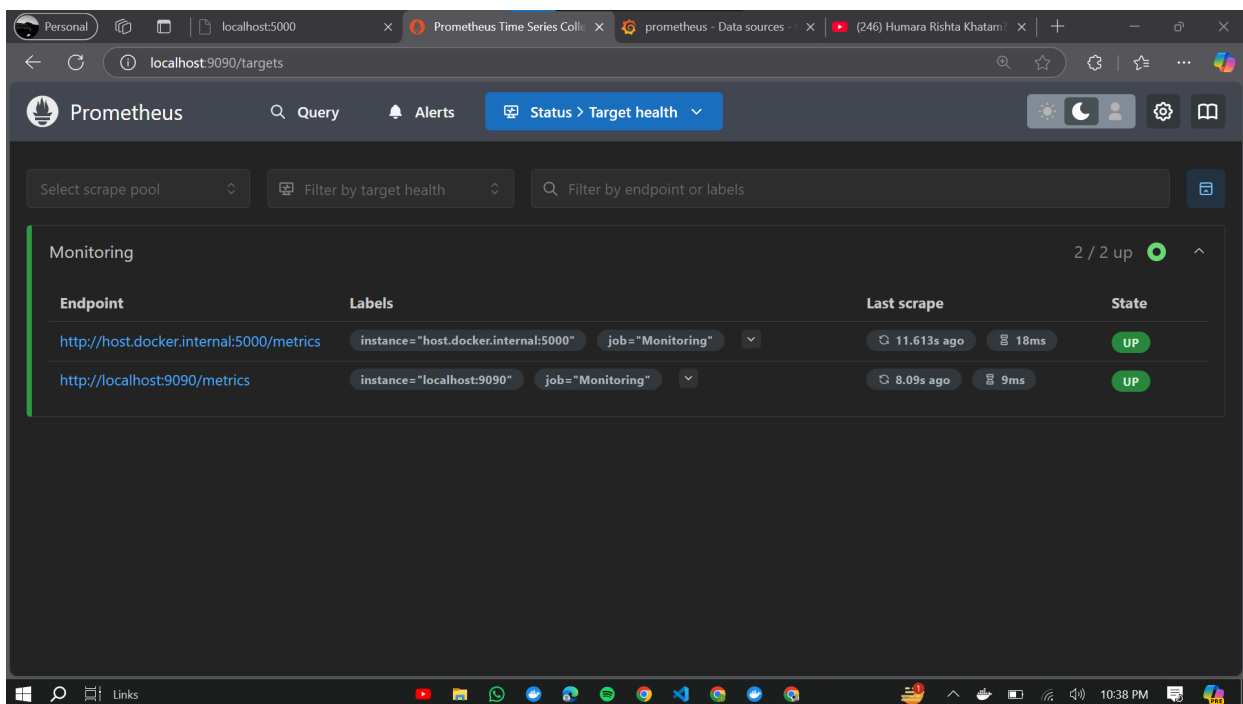
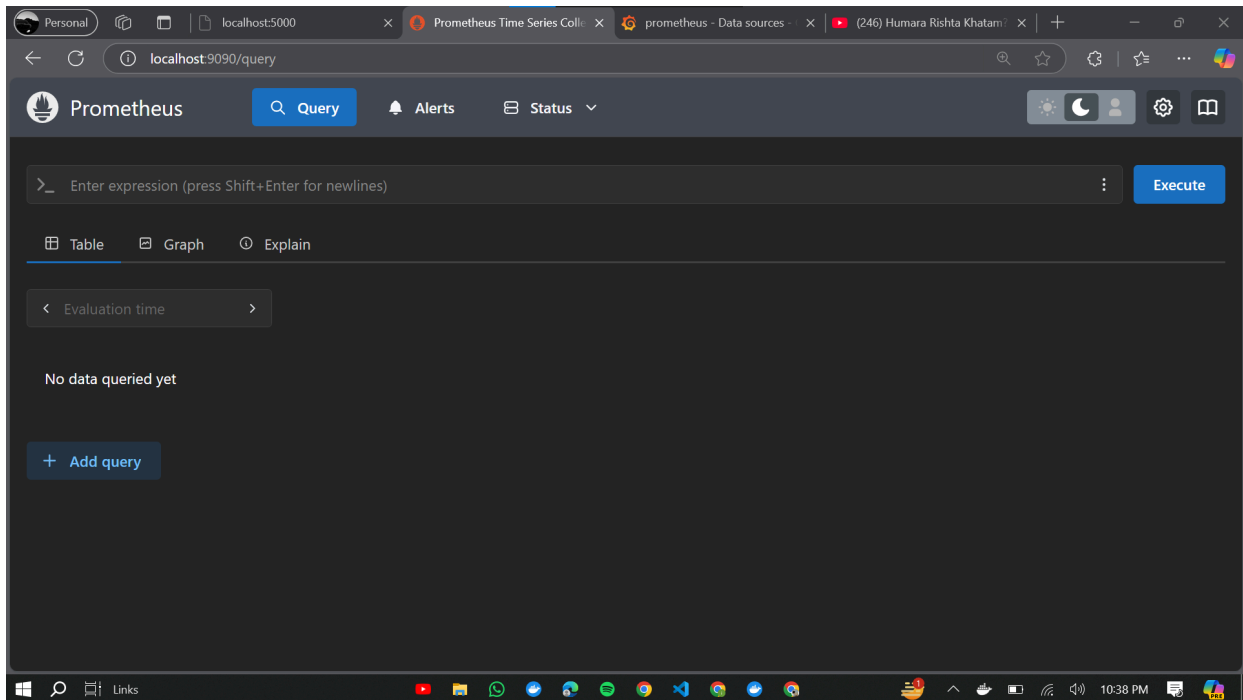
- Prometheus was installed and configured on the server hosting the Flask API.
- The `prometheus.yml` configuration file was updated to scrape metrics from the Flask API.

2. Exposing Metrics:

- The Flask API was integrated with the `prometheus-flask-exporter` library to expose metrics.
- Custom metrics were defined to monitor ML model-specific parameters, such as inference latency, request count, and error rates.

3. Scraping Metrics:

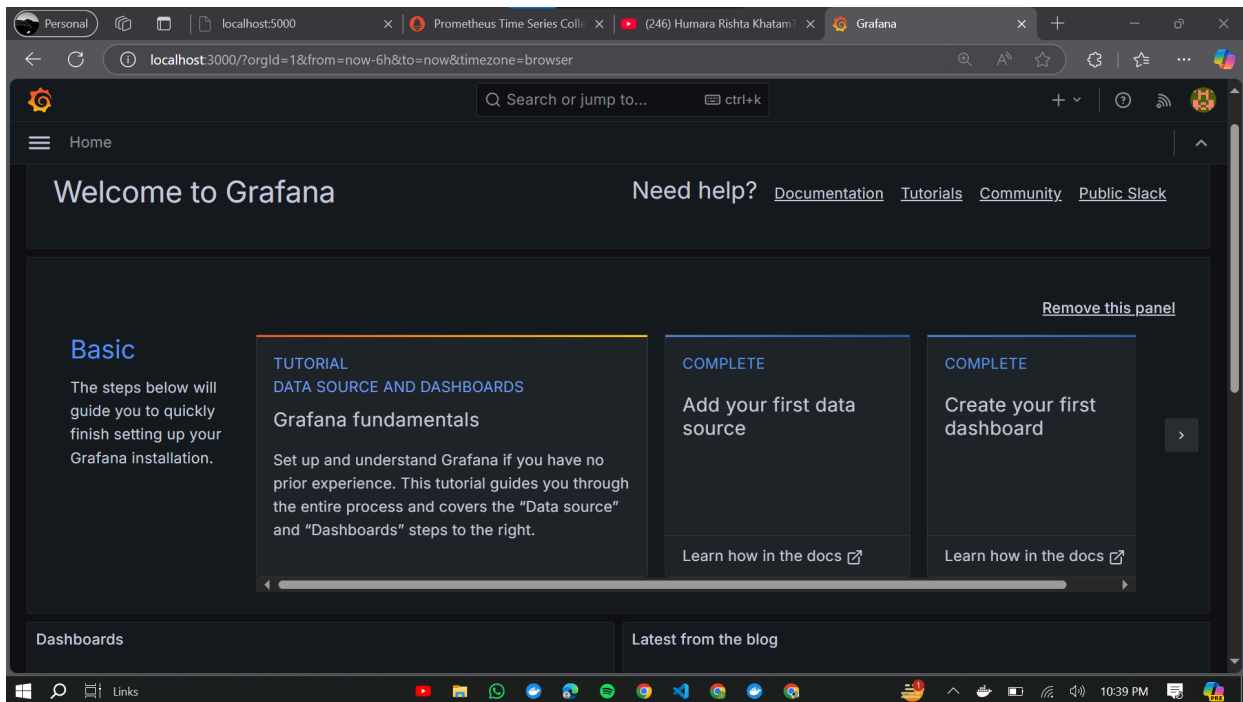
- Prometheus was configured to scrape metrics at regular intervals from the Flask API and system exporters (e.g., `node_exporter` for system metrics).

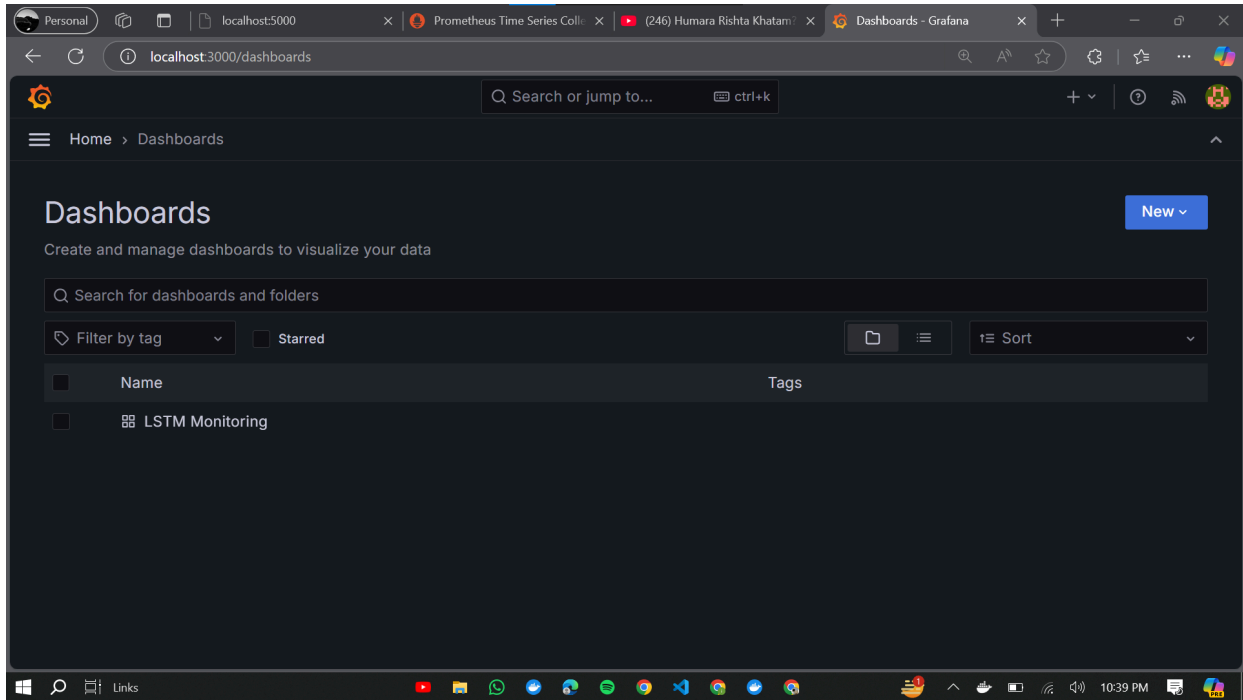


3.3. Grafana Setup

1. Installing Grafana:

- Grafana was installed on the same server as Prometheus for easy access.
- 2. Connecting to Prometheus:**
 - A Prometheus data source was added in Grafana to query metrics.
- 3. Creating Dashboards:**
 - Custom dashboards were created to display:
 - API Metrics: Request rates, latency, and error counts.
 - System Metrics: CPU usage, memory consumption, and disk IO.
 - Model Metrics: Prediction distribution, average inference time, and error rates.
- 4. Setting Up Alerts:**
 - Alerts were configured for critical conditions, such as high latency or high error rates, to ensure timely responses.

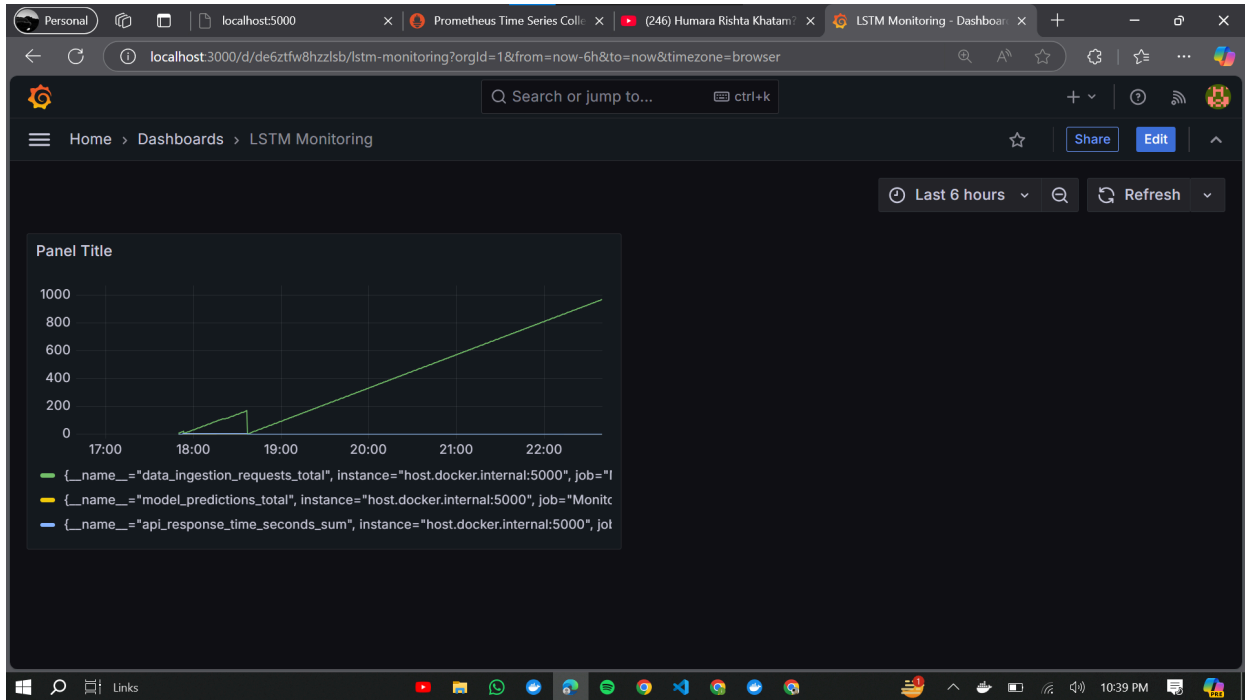




4. Metrics Monitored

The following metrics were monitored:

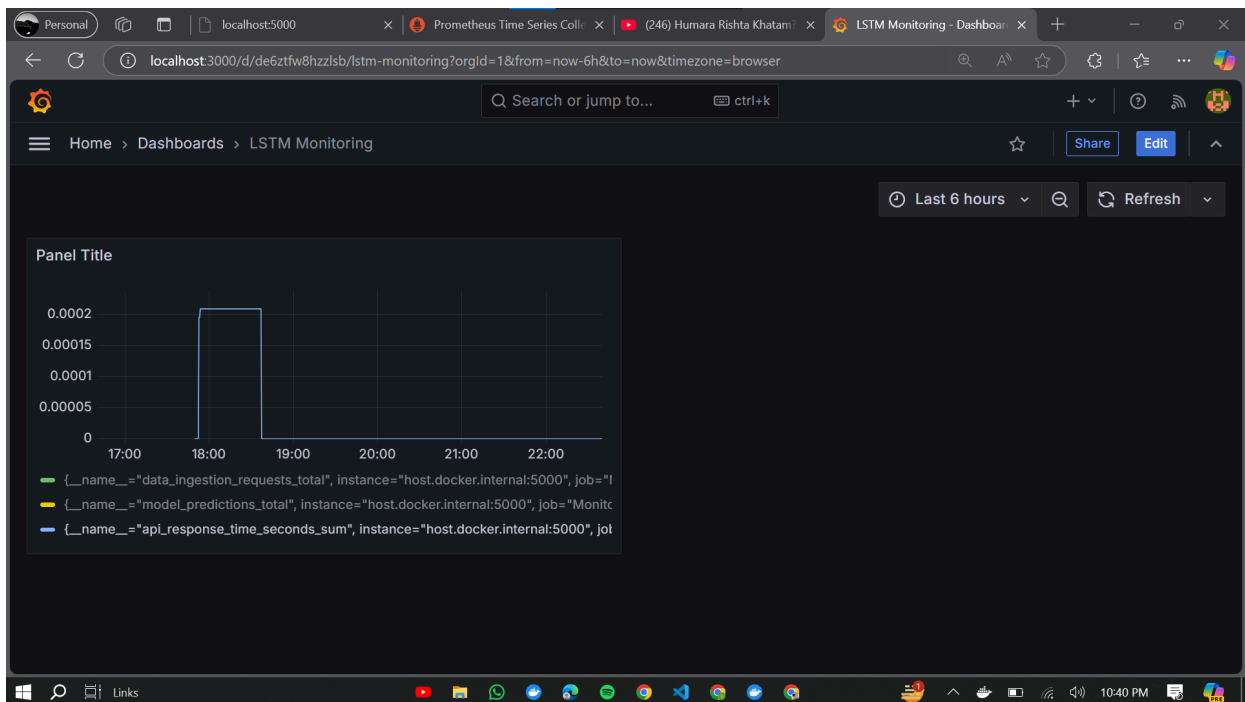
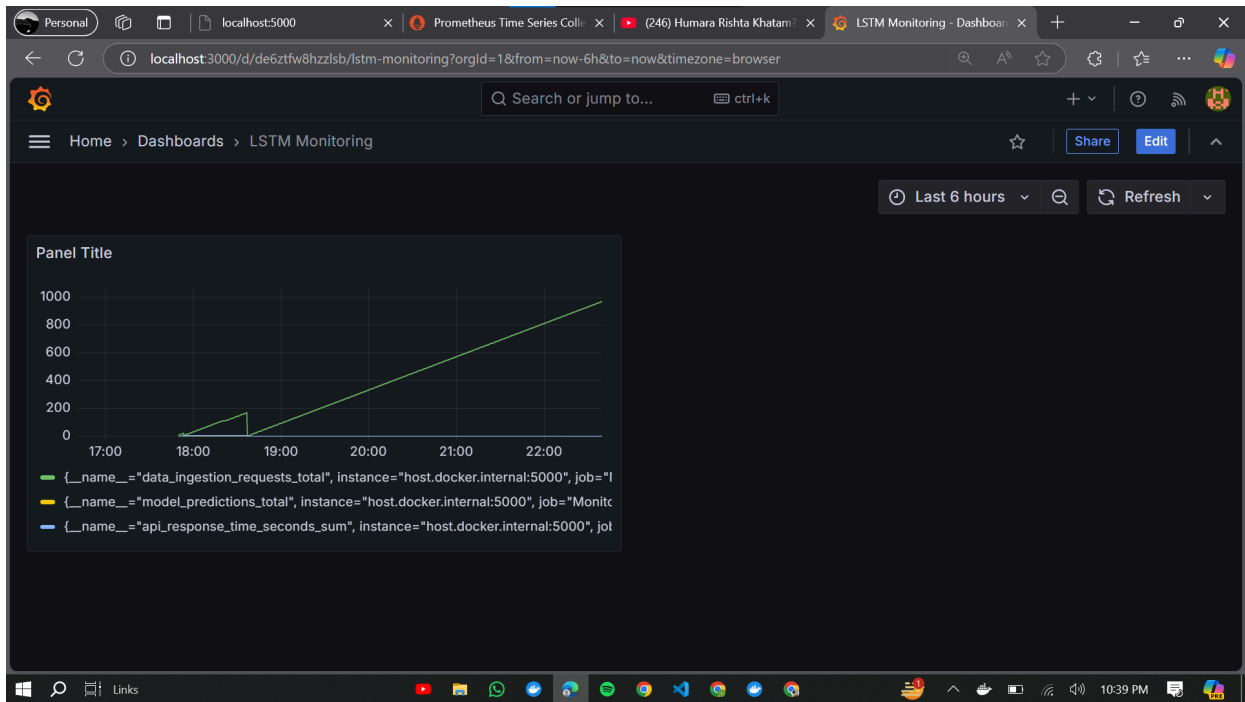
- **API Metrics:**
 - Total requests served.
 - Request latency (p95, p99 percentiles).
 - Success and error rates.
- **System Metrics:**
 - CPU and memory usage.
 - Disk utilization.
 - Network IO.
- **Model-Specific Metrics:**
 - Inference time per request.
 - Distribution of predictions.
 - Error rates based on model outputs.

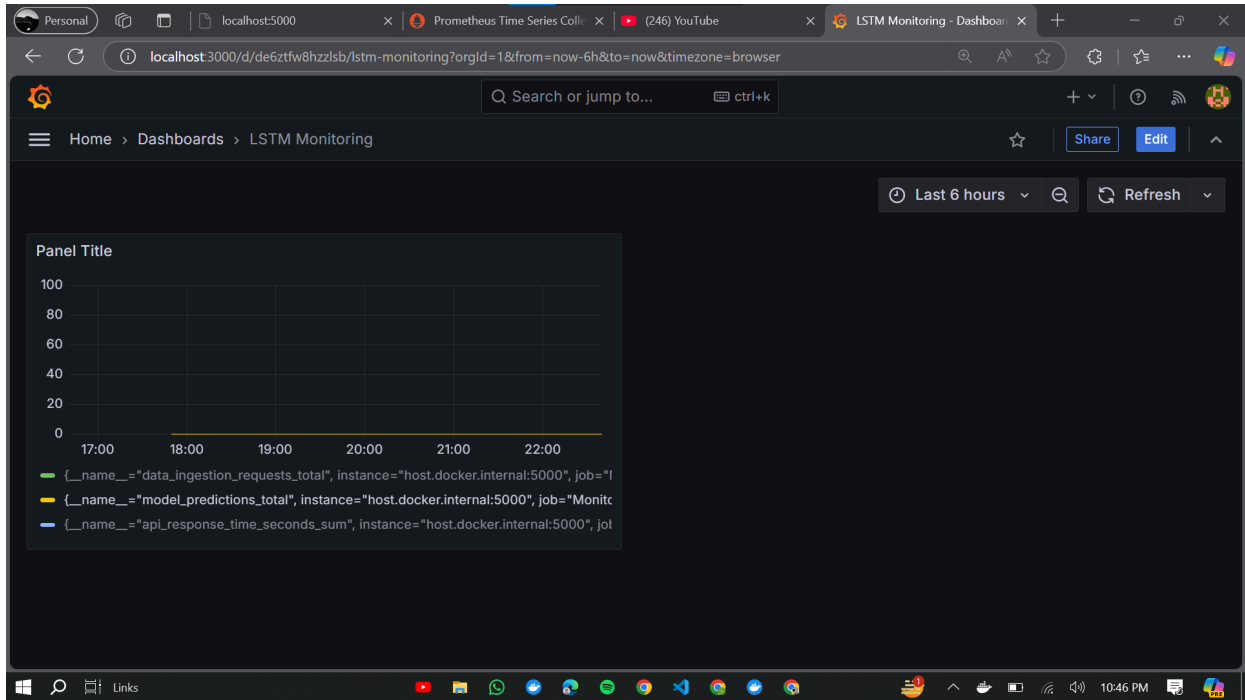


5. Results

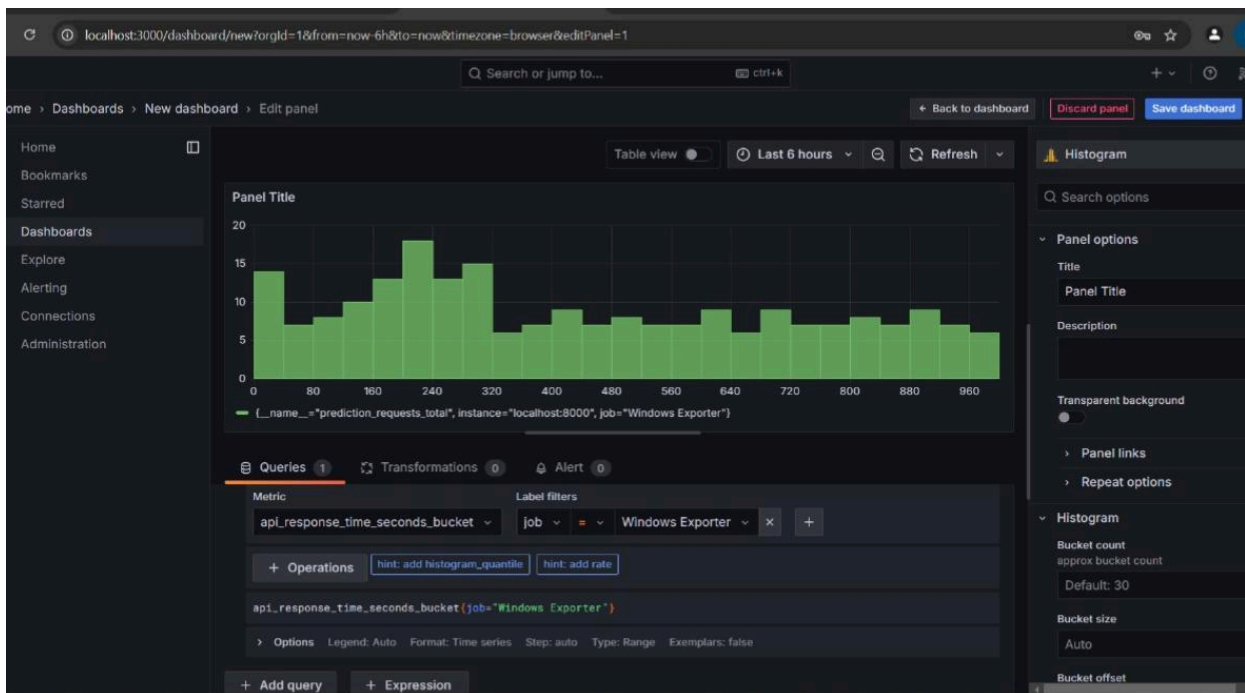
The monitoring setup successfully provided real-time visibility into the performance of the Flask API and the ML model. Key observations include:

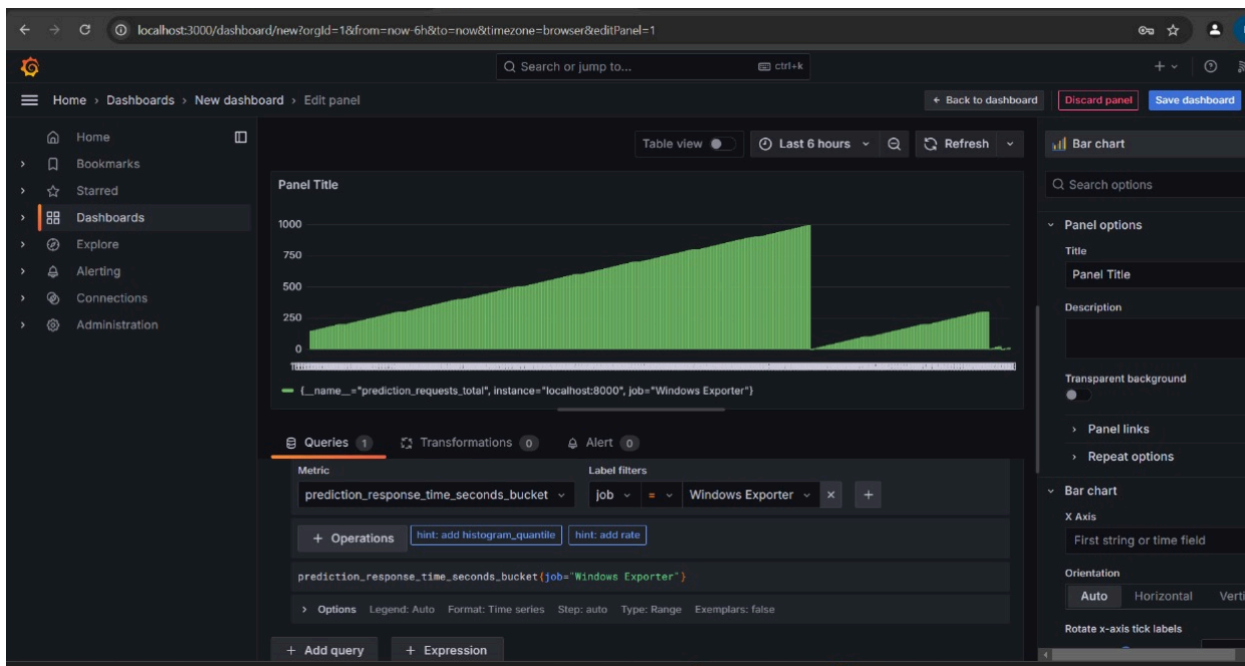
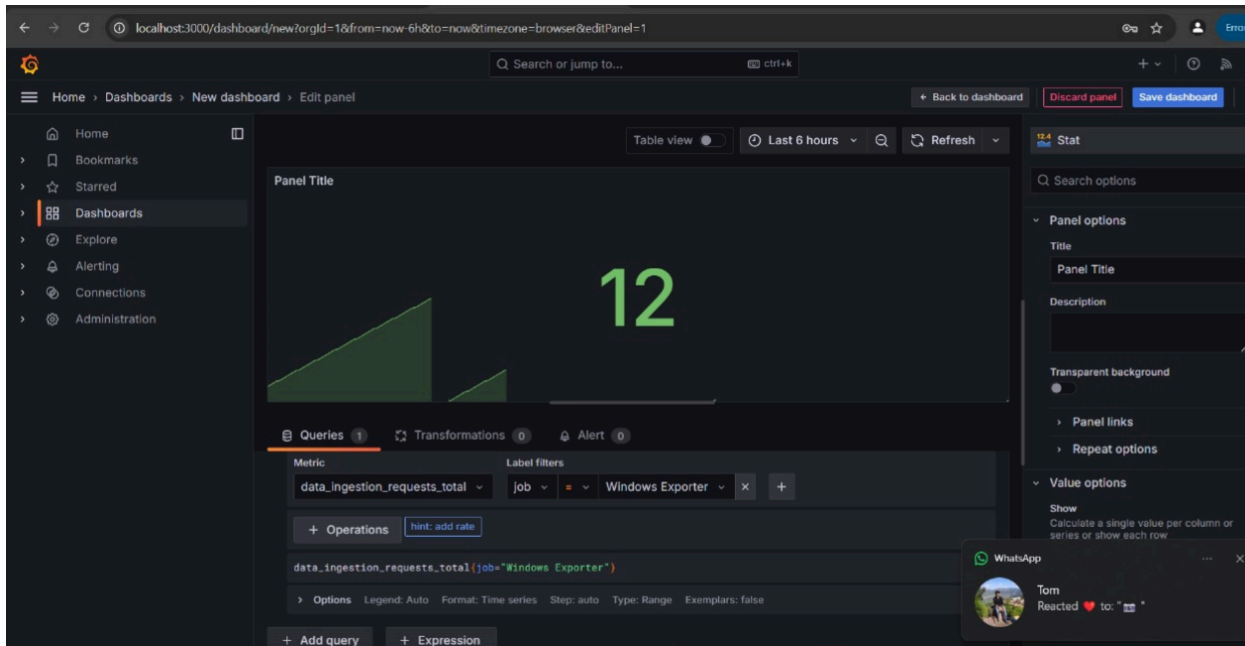
- Consistent response times under normal loads, with latency spikes during high traffic periods.
- Memory usage correlated with the size of input data processed by the model.
- Alerts for latency and error thresholds effectively notified stakeholders of potential issues.

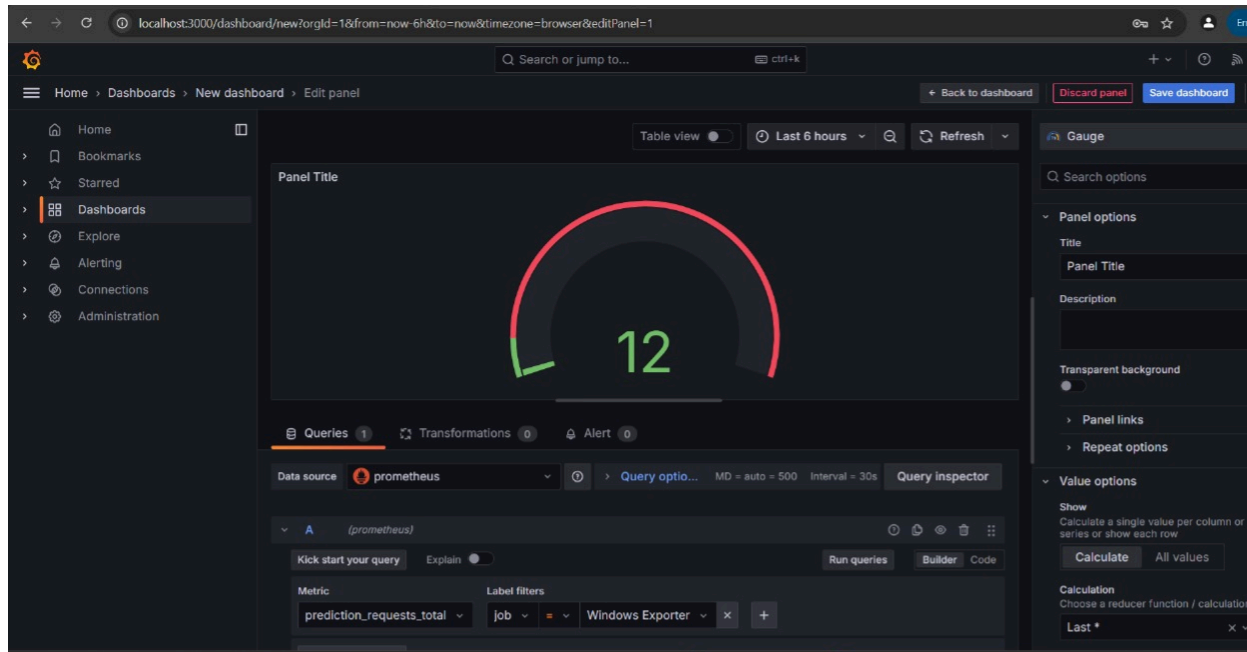




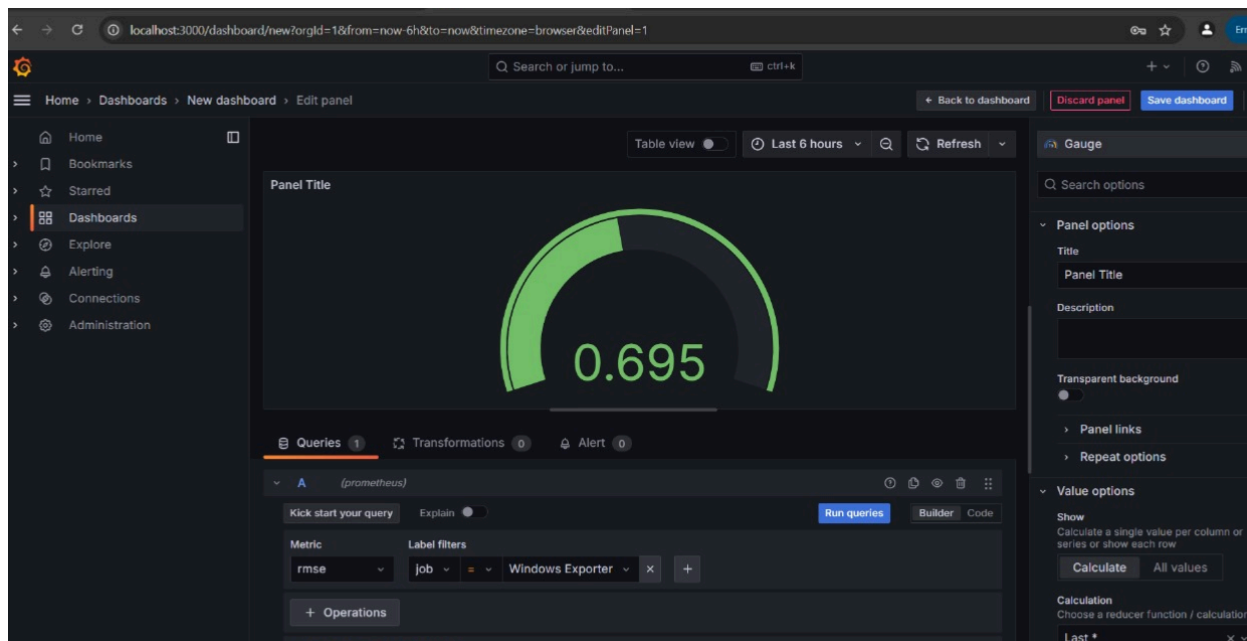
6. Task 3 Part 2-Performance







7. Task 3 Part 3 - Live Data Performance



8. Conclusion

The integration of Prometheus and Grafana provided an effective monitoring solution for the Flask API serving the ML model. This setup enables data-driven decision-making and ensures

the reliability of the deployed system. The use of real-time visualization and alerting mechanisms has improved the operational efficiency of the system.